Wtloss notebook

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Contents

Module 6 Lab Activity for PSY 652

Load Libraries

```
library(ppcor)
library(psych)
library(tidyverse)

## Warning: package 'ggplot2' was built under R version 3.6.3

## Warning: package 'tibble' was built under R version 3.6.3

## Warning: package 'tidyr' was built under R version 3.6.3

## Warning: package 'dplyr' was built under R version 3.6.3

## Warning: package 'forcats' was built under R version 3.6.3

library(olsrr)

## Warning: package 'olsrr' was built under R version 3.6.3

library(apaTables)
```

Import data

```
wtlossa <- read_csv("wtloss_parta.csv")
wtlossb <- read_csv("wtloss_partb.csv")</pre>
```

Merge data

```
wtloss<-merge(x=wtlossa, y=wtlossb,by="id")</pre>
```

Describe Data

Via base R's summary function

```
summary(wtloss)

## id lbslost caldef selfeff
## Min. : 1.00 Min. :-3.190 Min. :-2.266 Min. :-3.01976
```

```
## 1st Qu.: 25.75
                   1st Qu.: 1.623
                                   1st Qu.: 7.252
                                                   1st Qu.:-0.52594
## Median : 50.50
                   Median : 3.140
                                   Median :10.690
                                                   Median : 0.11935
## Mean : 50.50
                                                   Mean : 0.06383
                   Mean : 3.063
                                   Mean
                                        :10.804
## 3rd Qu.: 75.25
                   3rd Qu.: 4.697
                                   3rd Qu.:13.893
                                                   3rd Qu.: 0.71565
## Max. :100.00
                   Max. : 7.565
                                   Max.
                                          :23.572
                                                   Max.
                                                          : 2.71836
```

Via psych's describe function

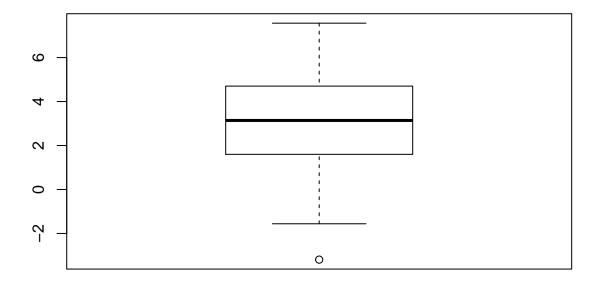
describe(wtloss)

```
n mean
                            sd median trimmed
                                               mad
                                                     \min
                                                            max range skew
          vars
## id
             1 100 50.50 29.01 50.50
                                      50.50 37.06 1.00 100.00 99.00 0.00
## lbslost
             2 100 3.06 2.10
                                 3.14
                                        3.12 2.31 -3.19
                                                           7.56 10.76 -0.32
## caldef
             3 100 10.80 5.14 10.69
                                        10.86 4.90 -2.27 23.57 25.84 -0.07
## selfeff
             4 100 0.06 1.11
                                 0.12
                                        0.07 0.95 -3.02
                                                           2.72 5.74 -0.16
##
          kurtosis
## id
             -1.24 2.90
## lbslost
             -0.32 0.21
## caldef
              0.01 0.51
## selfeff
              0.33 0.11
```

Look for outliers with boxplots

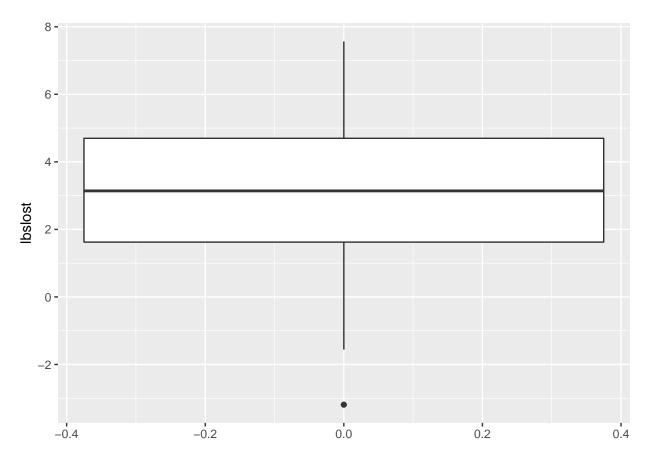
Via Base R's boxplot function

```
boxplot(wtloss$lbslost)
```



$\label{eq:Via ggplot2} \mbox{Via ggplot2's ggplot function}$

```
ggplot(wtloss, aes(y = lbslost)) +
  geom_boxplot()
```

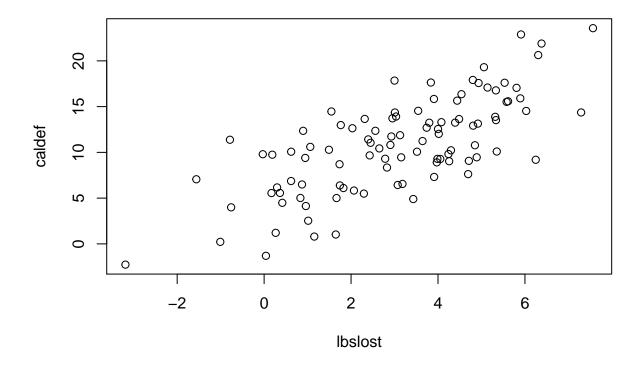


The boxplot indicates that there is one outlier for lbslost, with a value of -4. This indicates that one participant gained 4 pounds during the course of this study.

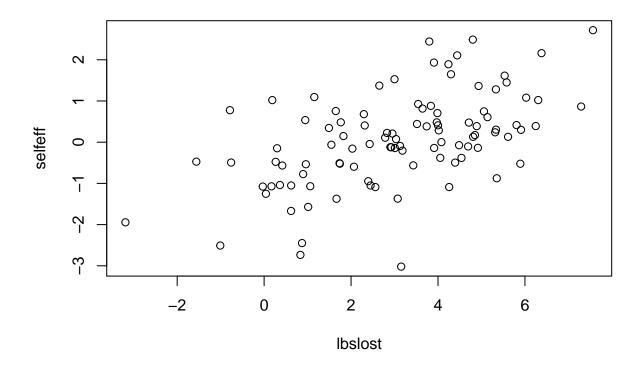
Plot relationships between variables

Via Base R's plot function

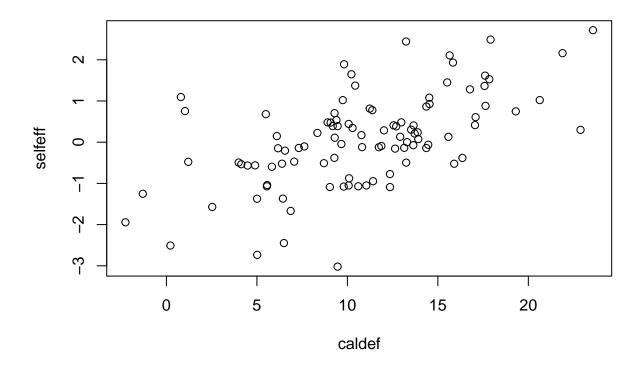
```
attach(wtloss)
plot(lbslost, caldef )
```



plot(lbslost, selfeff)



plot(caldef , selfeff)

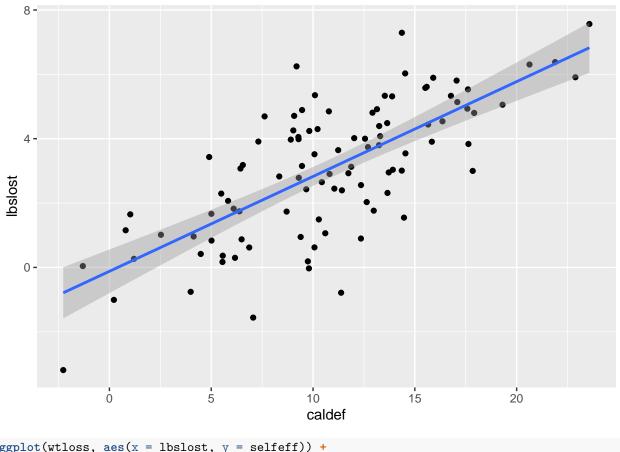


detach(wtloss)

Via ggplot2's ggplot function

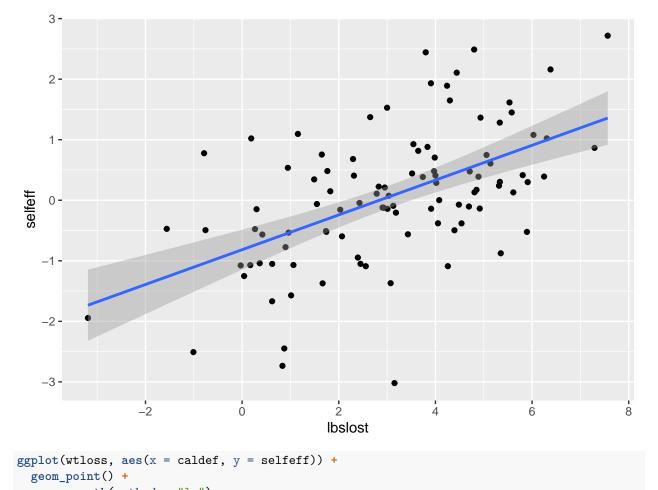
```
ggplot(wtloss, aes(x = caldef, y = lbslost)) +
  geom_point() +
  geom_smooth(method = "lm")
```

$geom_smooth()$ using formula 'y ~ x'



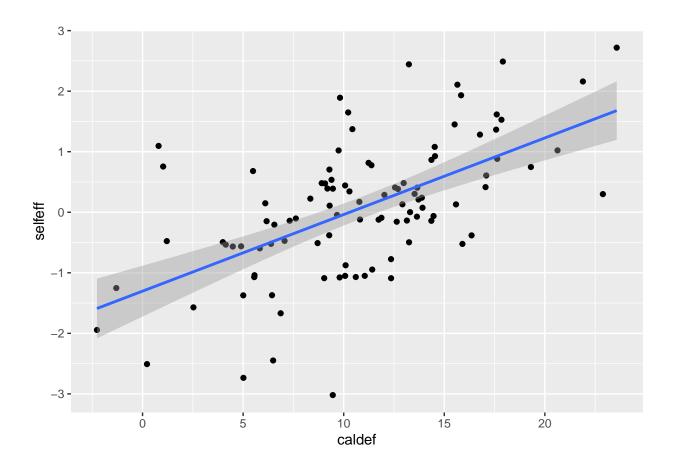
```
ggplot(wtloss, aes(x = lbslost, y = selfeff)) +
  geom_point() +
  geom_smooth(method = "lm")
```

$geom_smooth()$ using formula 'y ~ x'



geom_smooth(method = "lm")

$geom_smooth()$ using formula 'y ~ x'



Correlations

Pearson's Correlations Matrices

Via Base R's cor function

```
cor(wtloss)

## id lbslost caldef selfeff

## id 1.00000000 -0.1425016 -0.07237732 -0.05700845

## lbslost -0.14250157 1.0000000 0.72174587 0.54278360

## caldef -0.07237732 0.7217459 1.00000000 0.58508654

## selfeff -0.05700845 0.5427836 0.58508654 1.00000000
```

Via apaTables' apa.cor.table function

```
apa.cor.table(wtloss, "wtloss correlations.doc", show.conf.interval = TRUE)
##
##
## Means, standard deviations, and correlations with confidence intervals
##
##
                                         2
##
     Variable
                М
                      SD
                                                    3
##
     1. id
                50.50 29.01
##
```

```
##
     2. lbslost 3.06 2.10 -.14
##
                             [-.33, .06]
##
     3. caldef 10.80 5.14
                            -.07
##
                                         .72**
##
                             [-.27, .13] [.61, .80]
##
                                                    .59**
     4. selfeff 0.06 1.11 -.06
                                         .54**
##
                             [-.25, .14] [.39, .67] [.44, .70]
##
##
##
## Note. M and SD are used to represent mean and standard deviation, respectively.
## Values in square brackets indicate the 95% confidence interval.
## The confidence interval is a plausible range of population correlations
## that could have caused the sample correlation (Cumming, 2014).
## * indicates p < .05. ** indicates p < .01.
##
```

Correlation coefficients measure the direction and strength of the tendnecy for two variables to vary together. Correlation coefficients do not apply causation.

The correlation coefficient between lbslos and caldef is .72, and this is significant at p<0.01. Thus, there is a strong, positive (uphill) correlation between lbslost and caldef.

The correlation coefficient between lbslost and selfeff is .54, and this is significant at p<0.01. Thus, there is a strong, positive (uphill) correlation between lbslost and selfeff.

The correlation between caldef and selfeff is .59, and this is significant at p<0.01. Thus, there is a strong, positive (uphill) correlation between caldef and selfeff.

The correlation between lbslost and caldef is larger than the correlations between lbslost and selfeff and between caldef and selfeff.

Get partial correlation

```
attach(wtloss)
pcor.test(lbslost, caldef, selfeff)

## estimate p.value statistic n gp Method
## 1 0.5933978 9.634079e-11 7.260806 100 1 pearson
detach(wtloss)
```

Partial correlation first removes from both the outcome (lbslost) and predictor (caldef) all variance which may be accounted for by a third variable (in this case selfeff). Then it correlates the remaining variance of caldef with the remaining variance of lbslost. Here, the partial correlation between lbslost and caldef is .593 and this is significant at p<0.01. Thus, there is still a strong, positive (uphill) correlation between lbslost and caldef when controlling for or holding constant the effects of selfeff. This correlation is smaller than when the effects of selfeff were not removed (.593 compared to 0.722).

Get semipartial correlation

```
attach(wtloss)
spcor.test(lbslost, caldef, selfeff)

## estimate    p.value statistic    n gp Method
## 1 0.4983786 1.525307e-07    5.661694 100    1 pearson
```

detach(wtloss)

Semi-partial correlation first removes from the predictor (caldef) all variance which may be accounted for by the other predictors (in this case selfeff). Then it correlates the remaining variance of the predictor (caldef) with y (lbslost). Here the semi-partial correlation between caldef and lbslost is .498, and this is significant at p<0.01. Thus, there is still a positive (uphill) relationship between lbs and caldef, but this correlation is smaller (now moderately strong; 0.498 compared to 0.722) than when the effects of selfeff on caldef were not controlled for.

Note: the semi-partial correlation is often considered to be a better indicator of the "actual relevance" of a predictor, because it is scaled relative the total variability of the outcome variable. The squared semi-partial correlation will give you the proportion of unique variance accounted for by the predictor, relative to the total variance of Y. This is a key concept in Multiple Linear Regression models.

Fit a Simple Linear Regression (SLR) Model

```
mod1 <- lm(lbslost ~ caldef, data = wtloss)</pre>
```

Display SLR model results

Via base R's summary function

```
summary(mod1)
```

```
##
## Call:
## lm(formula = lbslost ~ caldef, data = wtloss)
##
## Residuals:
##
       Min
                1Q
                   Median
                                3Q
  -4.0197 -0.9480 0.0838
##
                           1.1227
                                    3.6602
##
## Coefficients:
               Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) -0.12079
                           0.34127
                                    -0.354
                                               0.724
## caldef
                0.29473
                           0.02855
                                    10.323
                                              <2e-16 ***
## ---
## Signif. codes:
                     '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 1.46 on 98 degrees of freedom
## Multiple R-squared: 0.5209, Adjusted R-squared: 0.516
## F-statistic: 106.6 on 1 and 98 DF, p-value: < 2.2e-16
```

Via olsrr's ols_regress function

ols_regress(mod1)

##	Model Sur	Model Summary				
##						
## R	0.722	RMSE	1.460			
## R-Squared	0.521	Coef. Var	47.647			
## Adj. R-Squared	0.516	MSE	2.131			
## Pred R-Squared	0.504	MAE	1.149			

## ## ## ## ##	RMSE: Root Mean Square Error MSE: Mean Square Error MAE: Mean Absolute Error ANOVA									
## ## ## ##		Sum of Squares	DF M	lean Square	F	Sig.				
## ##	Regression Residual Total	227.034 208.801			106.558	0.0000				
## ## ##	Parameter Estimates									
##	model	Beta		Std. Beta		_		upper		
##	(Intercept)	-0.121	0.341	0.722	-0.354	0.724	-0.798	0.556		

The beta for a predictor represents the expected change in y for a 1-unit increase in x. Here, the beta for caldef is 0.295, indicating that lbslost is expected to increase by 0.295 for every 1-unit increase in caldef. The standard error for this estimate is 0.029, indicating that the average distance that the observed values fall from the predicted regression line is 0.029. The upper and lower confidence intervals for this value indicate that there is a 95% liklihood that the true value for this beta estimate falls between 0.238 and 0.351. Because the 95% confidence interval for the estimate does not include zero, and because p < 0.001, this effect is significant.

The model R^2 value represents the proportion of variability in y that the model explains. Here, the model R^2 is 0.521, indicating that the predictor (caldef) explains 52.1% of the variability in lbslost.